Sentiment Analysis on Amazon Fine Food Reviews

Mt. SAC CISB 62 Final Project - Fall 2023

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https://github.com/rmoon64/CISB62_Final/ (https://github.com/rmoon64/CISB62_Final/)

Introduction / Summary:

The 'Amazon Fine Food Reviews' from Kaggle is a complete dataset that has about 560,000 reviews, which we trim down to 50,000 reviews. The goal of the project is to recommend new products to someone who does reviews often (Chris), using RNN to perform sentimental analysis using only Amazon reviews as the model.

This project utilized various deep learning techniques. The main tools used were RNN, TensorFlow V1, and hyperparameter tuning. First, I utilized a trimmed-down version of the data set with 50,000 reviews. Then, I used Matplotlib to plot the visualizations of important data, for example, the top 10 products with the most reviewers and the percentage of positive and negative reviews made by Chris. I then prepared the RNN with the LSTM model. This model was then fitted using six epochs and a batch size of twenty. This proved to be very beneficial, as the accuracy was extremely high at 0.9953 with a quite low loss of 0.0160. Next, I cleaned the data and defined the parameters and placeholders. Lastly, I got the scores and recommendations for Chris.

https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews (https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews)

```
In [1]:
            import tensorflow as tf
            import seaborn as sns
            import re
            import pandas as pd
            import numpy as np
            import keras
            import datetime
            from tensorflow.keras.preprocessing.sequence import pad_sequences
            from tensorflow.keras.preprocessing import sequence
            from tensorflow.keras.models import Sequential
            from tensorflow.keras.layers import Dense, LSTM, Embedding
            from tensorflow.keras.callbacks import ModelCheckpoint
            from string import punctuation
            from sklearn.model_selection import train_test_split
            from nltk.corpus import stopwords
            from matplotlib import pyplot as plt
            from keras.preprocessing.text import Tokenizer
            WARNING:tensorflow:From C:\Anaconda\Lib\site-packages\keras\src\losses.p
            y:2976: The name tf.losses.sparse softmax cross entropy is deprecated. P
            lease use tf.compat.v1.losses.sparse softmax cross entropy instead.
In [2]: ▶ import warnings
            warnings.filterwarnings("ignore")
In [3]:
        #Import dataset
            df = pd.read csv('Reviews.csv')

    df.describe()
In [4]:
   Out[4]:
```

	ld	HelpfulnessNumerator	HelpfulnessDenominator	Score	
count	50000.000000	50000.000000	50000.000000	50000.000000	5.00000
mean	25000.500000	1.603360	2.060260	4.145840	1.29519
std	14433.901067	5.620771	6.216044	1.325596	4.73462
min	1.000000	0.000000	0.000000	1.000000	9.61718
25%	12500.750000	0.000000	0.000000	4.000000	1.26964
50%	25000.500000	0.000000	1.000000	5.000000	1.30913
75%	37500.250000	2.000000	2.000000	5.000000	1.33107
max	50000.000000	398.000000	401.000000	5.000000	1.35121
4					

```
In [5]:

    df.head(3)

   Out[5]:
               ld
                     ProductId
                                         Userld ProfileName HelpfulnessNumerator HelpfulnessDo
               1 B001E4KFG0 A3SGXH7AUHU8GW
                                                  delmartian
                                                                            1
                2 B00813GRG4
                                A1D87F6ZCVE5NK
                                                                            0
                                                      dll pa
                                                     Natalia
                                                     Corres
             2 3 B000LQOCH0
                                 ABXLMWJIXXAIN
                                                                            1
                                                    "Natalia
                                                    Corres"
In [6]:

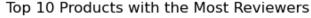
    df.info()
            <class 'pandas.core.frame.DataFrame'>
            RangeIndex: 50000 entries, 0 to 49999
            Data columns (total 10 columns):
             #
                 Column
                                          Non-Null Count Dtype
                  ----
            - - -
                                           -----
                                                           ----
             0
                 Ιd
                                          50000 non-null
                                                           int64
             1
                 ProductId
                                          50000 non-null object
             2
                 UserId
                                          50000 non-null object
             3
                 ProfileName
                                          49995 non-null
                                                           object
             4
                 HelpfulnessNumerator
                                          50000 non-null
                                                           int64
                 HelpfulnessDenominator
             5
                                          50000 non-null int64
             6
                 Score
                                          50000 non-null int64
             7
                 Time
                                          50000 non-null
                                                          int64
             8
                 Summary
                                          49998 non-null
                                                          object
             9
                 Text
                                          50000 non-null
                                                           object
            dtypes: int64(5), object(5)
            memory usage: 3.8+ MB
In [7]: ▶ print(df.shape)
            (50000, 10)
```

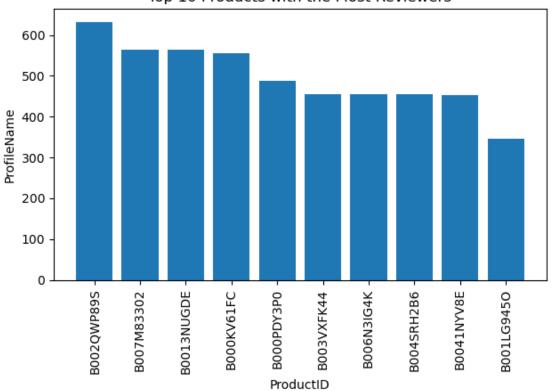
In [8]: ▶	df.	. hea	ad()						
Out[8]:		ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	HelpfulnessE		
	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1			
	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0			
	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1			
	3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3			
	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0			
	4						•		
In [9]: ▶	df	"Te	ext"][0]						
Out[9]:	'I have bought several of the Vitality canned dog food products and have found them all to be of good quality. The product looks more like a stew than a processed meat and it smells better. My Labrador is finicky and s he appreciates this product better than most.'								
n [10]: 🕨	<pre>#Grabbing the columns that we need df_reviews = df[['ProductId','ProfileName','Score','Text','HelpfulnessNume</pre>								

```
▶ #Loading the top 10 reviewers with the most reviews.
In [11]:
             df.pivot_table(columns=['ProfileName'], aggfunc='size').sort_values(ascender)
   Out[11]: ProfileName
             Gary Peterson
                                                        44
             C. F. Hill "CFH"
                                                        39
             O. Brown "Ms. O. Khannah-Brown"
                                                        35
                                                        35
             c2
             Gunner
                                                        31
             Chris
                                                        31
             Rebecca of Amazon "The Rebecca Review"
                                                        29
                                                        24
             Laura
             Amanda
                                                        24
             Mike
                                                        24
             dtype: int64
In [12]:
         ▶ popular = df[['ProductId','ProfileName']].groupby('ProductId').count().sor
          ▶ df.columns
In [13]:
             Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerato
   Out[13]:
                     'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
                   dtype='object')
```

Visuals: matplotlib and seaborn

```
In [14]: ► top_10_popular = popular.head(10) # Select the top 10 products with the mc
```





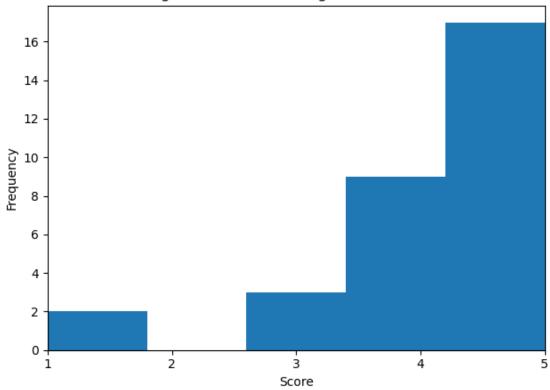
Out[16]: ProductId ProfileName Score Text Help

151	B00374XSVY	Chris	5	Works with chicken fish beef or pork. Fast eas
637	B000G6RYNE	Chris	4	This kettle chips taste "Good , Crispy & Crunc
729	B008BEGP9W	Chris	4	I really like the pineapple shortcakes sold he
1006	B002XG21MO	Chris	5	These are just like the animal crackers we eat
3142	B000FDKQCY	Chris	5	This product is as good as any that I have eve
5301	B003OJLCXI	Chris	4	I really like this tea, but my husband smelled
5826	B000633O2C	Chris	5	I want to give my cats as much variety as poss
7424	B005LMLXN0	Chris	5	As a tea-junkie, Runa's traditional guayusa of
7653	B000TRFGGM	Chris	4	I opened the carton and the plant looked like
7812	B00474H936	Chris	4	I have tried almost every kind of "fake meat"
9712	B001LXYA5Q	Chris	4	This stuff works, but be warned the effect doe
14414	B00063KO34	Chris	5	My dogs love these chews. I have 5 dogs - all
15075	B00113L7KC	Chris	5	I love this tea. I don't profess to be a tea
15150	B0013E21V8	Chris	5	Our family loves this syrup! I love that it i
16240	B007TJGZ54	Chris	5	Love the Green Mountain Coffee; tastes great i
16546	B003P7WLF2	Chris	1	I purchased these in lieu of the V8 Fusions si
18674	B00008JOL0	Chris	5	Zuke's is the best and my dog loves to eat the
21217	B002QWP89S	Chris	5	Molly and Cocoa, our cocker spaniels, said to
21607	B002QWP89S	Chris	5	I am happy with the service of this company
26212	B0058AMY74	Chris	4	This kettle chips taste "Good , Crispy & Crunc
26717	B001IZG6P4	Chris	5	These are the best peppercorns for the money I
30041	B000DZFMEQ	Chris	5	My wife is gluten and dairy intolerant and we
32735	B0083QJU72	Chris	3	Having grown up in sugar maple country and bou
36181	B000ILKXP8	Chris	3	I've seen some reviewers commenting on the sug
38414	B002QK0RJG	Chris	5	

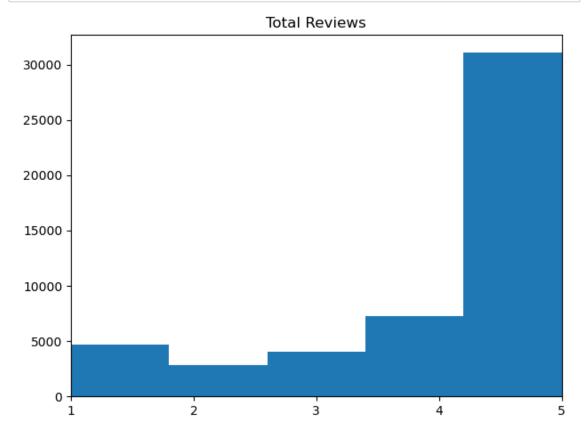
4

Plotting Chris' percentage of positive views vs negative reviews

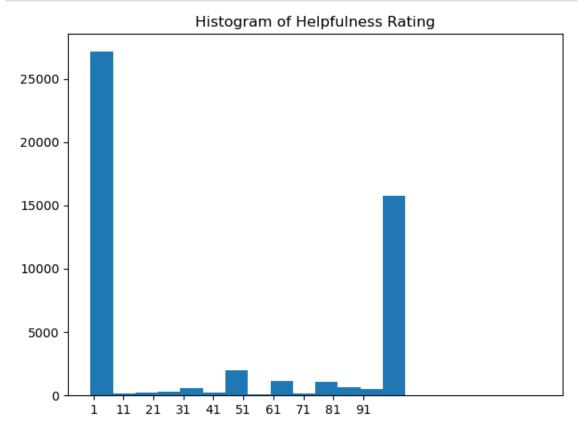
Percentage of Positive and Negative Reviews for Chris



Plotting the total reviews



Histogram of helpfulness rating



```
▶ | sns.countplot(data = df_reviews, x= 'Polarity_Rating')
In [23]:
   Out[23]: <Axes: xlabel='Polarity_Rating', ylabel='count'>
               40000
               35000
               30000
               25000
               20000
               15000
               10000
         In [24]:
   Out[24]: 11582
In [25]:

    data_Positive = df_reviews[df_reviews['Polarity_Rating'] == 'Positive'][0:

            data_Negative = df_reviews[df_reviews['Polarity_Rating'] == 'Negative']
            data_Negative_over = data_Negative.sample(20000, replace=True)
            df balance reviews = pd.concat([data Positive, data Negative over], axis=€
            import nltk
In [26]:
            nltk.download('stopwords')
            [nltk_data] Downloading package stopwords to
            [nltk data]
                           C:\Users\RL\AppData\Roaming\nltk data...
                         Package stopwords is already up-to-date!
            [nltk_data]
   Out[26]: True
In [27]: ► #Setting the stop words
            english_stops = set(stopwords.words('english'))
```

```
In [28]:

    df = df_balance_reviews

                                 # Reviews/Input
            x data = df['Text']
            y_data = df['Polarity_Rating'] # Sentiment/Output
            # PRE-PROCESS REVIEW
            x_data = x_data.replace({'<.*?>': ''}, regex = True)
                                                                       # remove htm
            x_data = x_data.replace({'[^A-Za-z]': ''}, regex = True) # remove nor
            x data = x data.apply(lambda review: [w for w in review.split() if w not i
            x_data = x_data.apply(lambda review: [w.lower() for w in review]) # Lower
            # ENCODE SENTIMENT -> 0 & 1
            y_data = y_data.replace('Positive', 1)
            ### simmilarly for y_data
            y data = y data.replace('Negative', 0)
In [29]:
        | X_train, X_test, y_train, y_test = train_test_split(x_data, y_data, test_s
In [30]:

    def get max length(x train):

                review_length = []
                for review in x_train:
                    review_length.append(len(review))
                return int(np.ceil(np.mean(review_length)))
         max_length = get_max_length(X_train)
In [31]:
            print(max length)
            48
         # ENCODE REVIEW
In [32]:
            token = Tokenizer(lower=False) # False becuase we already did it.
            token.fit_on_texts(X_train)
            x train = token.texts to sequences(X train)
            x_test = token.texts_to_sequences(X_test)
            ### this is the code to add the pad to x_train
            x_train = pad_sequences(x_train, maxlen=max_length, padding='post', trunca
            x_test = pad_sequences(x_test, maxlen=max_length, padding='post', truncati
            total_words = len(token.word_index) + 1 # we need to add 1 because of 0
```

```
In [33]: # ARCHITECTURE
EMBED_DIM = 3200
LSTM_OUT = 64

#### add the model here:
model = Sequential()

#model.add(Embedding(input_dim=max_length, output_dim=LSTM_OUT,input_lengt)
model.add(Embedding(total_words, EMBED_DIM, input_length = max_length))
model.add(LSTM(LSTM_OUT))
model.add(Dense(units=1, activation='sigmoid'))

### compile the model using: optimizer = 'adam', loss = 'binary_crossentra'
model.compile(optimizer='adam', loss='binary_crossentra'
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accu
#Adding a Checkpoint to save the model.
checkpoint = ModelCheckpoint('models/LSTM.h5', monitor='accuracy', save_be
```

WARNING:tensorflow:From C:\Anaconda\Lib\site-packages\keras\src\backend. py:873: The name tf.get_default_graph is deprecated. Please use tf.compa t.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Anaconda\Lib\site-packages\keras\src\optimize rs__init__.py:309: The name tf.train.Optimizer is deprecated. Please us e tf.compat.v1.train.Optimizer instead.

In [34]: ▶ | model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 48, 3200)	84083200
lstm (LSTM)	(None, 64)	835840
dense (Dense)	(None, 1)	65

Total params: 84919105 (323.94 MB)
Trainable params: 84919105 (323.94 MB)
Non-trainable params: 0 (0.00 Byte)

history = model.fit(x_train, y_train, epochs=6, batch_size=20, callbacks=

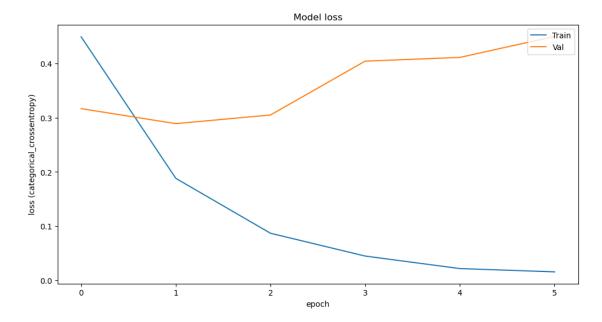
Epoch 1/6

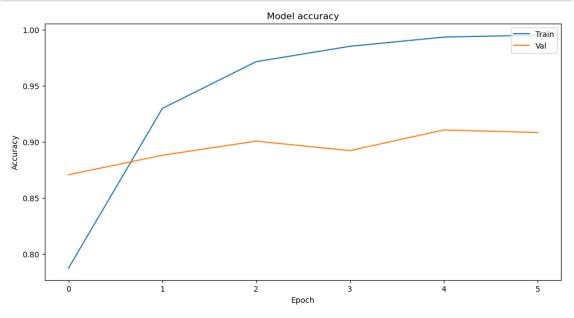
WARNING:tensorflow:From C:\Anaconda\Lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Pleas e use tf.compat.v1.ragged.RaggedTensorValue instead.

WARNING:tensorflow:From C:\Anaconda\Lib\site-packages\keras\src\engine\b ase_layer_utils.py:384: The name tf.executing_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing_eagerly_outside_functions instead.

```
curacy: 0.7871
Epoch 1: accuracy improved from -inf to 0.78708, saving model to models
\LSTM.h5
1300/1300 [============== ] - 722s 550ms/step - loss: 0.4
488 - accuracy: 0.7871 - val_loss: 0.3165 - val_accuracy: 0.8706
Epoch 2/6
curacy: 0.9298
Epoch 2: accuracy improved from 0.78708 to 0.92981, saving model to mode
ls\LSTM.h5
1300/1300 [==================== ] - 707s 544ms/step - loss: 0.1
882 - accuracy: 0.9298 - val_loss: 0.2889 - val_accuracy: 0.8880
Epoch 3/6
1300/1300 [================ ] - ETA: 0s - loss: 0.0871 - ac
curacy: 0.9716
Epoch 3: accuracy improved from 0.92981 to 0.97158, saving model to mode
ls\LSTM.h5
1300/1300 [============ ] - 834s 641ms/step - loss: 0.0
871 - accuracy: 0.9716 - val loss: 0.3048 - val accuracy: 0.9006
Epoch 4/6
curacy: 0.9853
Epoch 4: accuracy improved from 0.97158 to 0.98531, saving model to mode
ls\LSTM.h5
451 - accuracy: 0.9853 - val loss: 0.4040 - val accuracy: 0.8922
Epoch 5/6
1300/1300 [============== ] - ETA: 0s - loss: 0.0220 - ac
curacy: 0.9935
Epoch 5: accuracy improved from 0.98531 to 0.99354, saving model to mode
ls\LSTM.h5
1300/1300 [============= ] - 801s 616ms/step - loss: 0.0
220 - accuracy: 0.9935 - val loss: 0.4108 - val accuracy: 0.9106
Epoch 6/6
1300/1300 [================== ] - ETA: 0s - loss: 0.0160 - ac
curacy: 0.9953
Epoch 6: accuracy improved from 0.99354 to 0.99527, saving model to mode
ls\LSTM.h5
160 - accuracy: 0.9953 - val_loss: 0.4495 - val_accuracy: 0.9083
```

Out[36]: <matplotlib.legend.Legend at 0x238c30a1450>





```
In [38]: #I grab a random review from the dataframe
value = 200
df_reviews.iloc[value]

Out[38]: ProductId
B0028C4
```

```
ProfileName
Lou
Score
2
Text Even with small containers, they don't fill th...
HelpfulnessNumerator
0
HelpfulnessDenominator
0
Percent
0.0
Polarity_Rating Negative
Name: 200, dtype: object
```

```
df_reviews.iloc[value]['Text']
In [39]:
   Out[39]: "Even with small containers, they don't fill them up. These little tins
            are less than half filled and at the price charged it seems a rip-off. I
            s there some exotic ingredient as costly as gold contained in those tiny
            squares? Or how about the cereal ploy, they were filled at the factory
            but settled in transport.<br/>
<br/>
/>Can manufacturers be honest in their deal
            ings?"
In [40]:  review = df reviews.iloc[value]['Text']
            regex = re.compile(r'[^a-zA-Z\s]')
            review = regex.sub('', review)
            words = review.split(' ')
            filtered = [w for w in words if w not in english_stops]
            filtered = ' '.join(filtered)
            filtered = [filtered.lower()]
In [41]:
         tokenize words = token.texts to sequences(filtered)
            tokenize_words = pad_sequences(tokenize_words, maxlen=max_length, padding=
In [42]:  | result = model.predict(tokenize words)
            if result >= .50:
                print('Postive')
            else:
                print('Negative')
            Negative
         ▶ #Making an Unique Numeric ID for all the users
In [43]:
            df_reviews['UserID'] = pd.factorize(df_reviews['ProfileName'])[0] + 1
```

Out[44]:

		ProductId	ProfileName	Score	Text	HelpfulnessNumerator	HelpfulnessDen
_	151	B00374XSVY	Chris	5	Works with chicken fish beef or pork. Fast eas	0	
	637	B000G6RYNE	Chris	4	This kettle chips taste "Good , Crispy & Crunc	0	
	729	B008BEGP9W	Chris	4	I really like the pineapple shortcakes sold he	0	
	1006	B002XG21MO	Chris	5	These are just like the animal crackers we eat	0	
;	3142	B000FDKQCY	Chris	5	This product is as good as any that I have eve	0	
							•

In [45]: #I had to clean the data some more, some review went back and review the s
cleaned = df_reviews.drop_duplicates(subset=['ProductId', 'UserID'], keep=

print('Removed Dulipcated, Total Reviews {}'.format(cleaned.shape[0]))
print('Total Reviews {}'.format(df_reviews.shape[0]))

Removed Dulipcated, Total Reviews 49283 Total Reviews 50000

Productid ProfileName Score Text HelpfulnessNumerator HelpfulnessDenomin	In	[46]:	M	cle	eaned.h	ead()						
1 B00813GRG4 delmartian 5 Several of the Whality canned d Product arrived labeled as Jumbo Salted Peanut This is a confection of that has been around a least a labeled as Jumbo Salted Peanut This is a confection of that has been around a least a labeled as Jumbo Salted Peanut If you are looking for the secret a great laffy at a gre		Out[4	6]:		Proc	ductld	ProfileNam	ne Score	Text	HelpfulnessNum	nerator Helpfu	InessDenomin
1 B00813GRG4 dll pa 1 arrived labeled as Jumbo O Salted Peanut			0	B001E4	IKFG0	delmartia	an 5	bought several of the Vitality canned		1		
2 B000LQOCH0 Source Corres Corres Corres Lath as been around a fe 3 B000UA0QIQ Karl 2 Source Sourc			1	1 B00813GRG4 dll pa		pa 1	arrived labeled as Jumbo Salted	0				
3 B000UA0QIQ Karl 2 scret ingredient i 4 B006K2ZZ7K Bigham "M. Sigham "M.				2 B000LQO		OCH0	Corre "Natal	es ia	confection that has been around a	1		
### ### ##############################				3	B000UA	A0QIQ	Ka	arl 2	looking for the secret ingredient		3	
<pre>In [47]: user_rating_df = cleaned.pivot(index='UserID', columns='ProductId', values In [48]: user_rating_df.head(5) Out[48]: ProductId</pre>				4	B006K2	2ZZ7K	Bigham "N	Л. 5	taffy at a great price. There was a		0	
In [48]: user_rating_df.head(5) Out[48]: ProductId 2734888454 B00002NCJC B00002Z754 B00005V3DC B000084DVR B000084E1U UserID				4								•
Out[48]: ProductId 2734888454 B00002NCJC B00002Z754 B00005V3DC B000084DVR B000084E1U 0 NaN NaN NaN NaN NaN NaN 1 NaN NaN NaN NaN NaN NaN 2 NaN NaN NaN NaN NaN NaN 3 NaN NaN NaN NaN NaN NaN 4 NaN NaN NaN NaN NaN NaN	In	[47]:	H	use	er_rati	ng_df	= cleane	d.pivot	(index='Us	erID', colum	ns='Product	Id', values
UserID 0 NaN	In	[48]:	H	use	er_rati	ng_df	.head(5)					
0 NaN NaN NaN NaN NaN 1 NaN NaN NaN NaN NaN 2 NaN NaN NaN NaN NaN 3 NaN NaN NaN NaN NaN 4 NaN NaN NaN NaN NaN		Out[48]:		Pr		27348	88454 B00	002NCJC	B00002Z754	4 B00005V3DC	B000084DVR	B000084E1U
2NaNNaNNaNNaNNaN3NaNNaNNaNNaNNaNNaN4NaNNaNNaNNaNNaNNaN							NaN	NaN	NaN	NaN	NaN	NaN
3 NaN NaN NaN NaN NaN NaN NaN NaN NaN					1		NaN	NaN	NaN	NaN	NaN	NaN
4 NaN NaN NaN NaN NaN NaN					2		NaN	NaN	NaN	NaN	NaN	NaN
					3		NaN	NaN	NaN	NaN	NaN	NaN
5 rows × 6115 columns ▶					4		NaN	NaN	NaN	NaN	NaN	NaN
→				5 r	ows × 61	115 co	lumns					
				4								•

```
In [51]:  hiddenUnits = 20
             visibleUnits = len(user_rating_df.columns)
             vb = tf.compat.v1.placeholder("float", [visibleUnits])
             hb = tf.compat.v1.placeholder("float", [hiddenUnits])
             W = tf.compat.v1.placeholder("float", [visibleUnits, hiddenUnits])
             # Process phase 1 of a RBM, use v0, h0, h0
             v0 = tf.compat.v1.placeholder("float", [None, visibleUnits])
             h0 = tf.nn.sigmoid(tf.matmul(v0, W) + hb)
             h0 = tf.nn.relu(tf.sign( h0 - tf.random.uniform(tf.shape(input= h0))))
             #Phase 2: Reconstruction
             v1 = tf.nn.sigmoid(tf.matmul(h0, tf.transpose(W)) + vb)
             v1 = tf.nn.relu(tf.sign( v1 - tf.random.uniform(tf.shape(input= v1))))
             h1 = tf.nn.sigmoid(tf.matmul(v1, W) + hb)
             #Learning rate
             alpha = 1.0
             w pos grad = tf.matmul(tf.transpose(v0), h0)
             w_neg_grad = tf.matmul(tf.transpose(v1), h1)
             CD = (w_pos_grad - w_neg_grad) / tf.compat.v1.to_float(tf.shape(v0)[0])
             update w = W + alpha * CD
             update vb = vb + alpha * tf.reduce mean(v0 - v1, 0)
             update hb = hb + alpha * tf.reduce mean(h0 - h1, 0)
             err = v0 - v1
             err_sum = tf.reduce_mean(err * err)
             #Current weight
             cur w = np.zeros([visibleUnits, hiddenUnits], np.float32)
             cur_vb = np.zeros([visibleUnits], np.float32)
             cur hb = np.zeros([hiddenUnits], np.float32)
             prv w = np.zeros([visibleUnits, hiddenUnits], np.float32)
             prv_vb = np.zeros([visibleUnits], np.float32)
             prv hb = np.zeros([hiddenUnits], np.float32)
             sess = tf.compat.v1.Session()
             sess.run(tf.compat.v1.global_variables_initializer())
             # Using a for loop, Run the model, with 10 epochs, batchsize = 100, and er
             epochs = 10
             batchsize = 100
             errors = []
             for i in range(epochs):
                 for start, end in zip( range(0, len(trX), batchsize), range(batchsize)
                     batch = trX[start:end]
                     cur_w = sess.run(update_w, feed_dict={v0: batch, W: prv_w, vb: prv
                     cur vb = sess.run(update vb, feed dict={v0: batch, W: prv w, vb: p
```

```
cur_nb = sess.run(update_hb, feed_dict={v0: batch, W: prv_w, vb: prv_w = cur_w
    prv_vb = cur_vb
    prv_hb = cur_hb
errors.append(sess.run(err_sum, feed_dict={v0: trX, W: cur_w, vb: cur_print (errors[-1])
```

WARNING:tensorflow:From C:\Anaconda\Lib\site-packages\tensorflow\python \util\dispatch.py:1260: to_float (from tensorflow.python.ops.math_ops) i s deprecated and will be removed in a future version.

Instructions for updating:

Use `tf.cast` instead.

0.0025635296

0.0013016531

0.0009061099

0.0007227106

0.00061612227

0.00055364566

0.00051163853

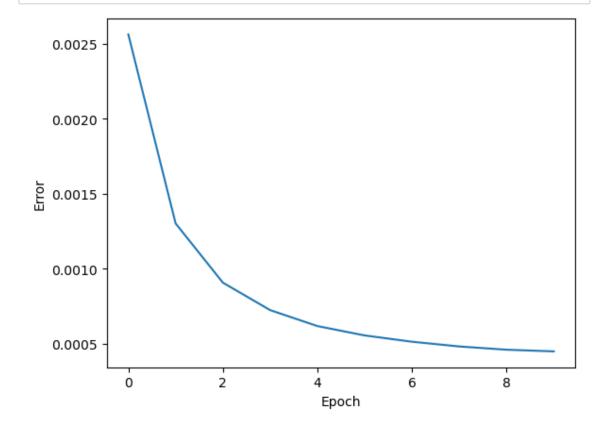
0.00048007743

0.00045839624

0.0004471017

In [52]: | plt.plot(errors) plt.ylabel('Error plt.ylabel('Error)

plt.ylabel('Error')
plt.xlabel('Epoch')
plt.show()



```
In [53]:
           ▶ mock user id = 151
In [54]:
             inputUser = trX[mock_user_id-1].reshape(1, -1)
              inputUser[0:5]
   Out[54]: array([[0., 0., 0., ..., 0., 0., 0.]])
In [55]: ▶ # Feeding in the user and reconstructing the input. use sigmoid
             hh0 = tf.nn.sigmoid(tf.matmul(v0, W) + hb)
             vv1 = tf.nn.sigmoid(tf.matmul(hh0, tf.transpose(W)) + vb)
             feed = sess.run(hh0, feed dict={ v0: inputUser, W: prv w, hb: prv hb})
             rec = sess.run(vv1, feed_dict={ hh0: feed, W: prv_w, vb: prv_vb})
             scored asin df mock = cleaned.drop duplicates(subset=['ProductId'])
In [56]:
              scored_asin_df_mock = scored_asin_df_mock.assign(RecommendationScore = rec
             scored asin df mock[['ProductId','RecommendationScore']].sort values(["Rec
   Out[56]:
                        ProductId RecommendationScore
               4063 B001EW5YQS
                                             0.025583
               7321
                      B0042395CA
                                             0.012464
              45379
                     B000FVVZ3U
                                             0.008445
              40981
                     B000IKEGRK
                                             0.005815
              36090
                     B002DHN1UE
                                             0.005210
              17705
                     B0010AR1E2
                                             0.004573
               5012
                    B000HDKZDC
                                             0.004495
              17240
                      B000I6PZVK
                                             0.004260
              14515
                     B0016814QO
                                             0.004161
                     B001RQAVKK
              33278
                                             0.004146
              29077
                     B000NU8H0C
                                             0.004062
               2950
                     B003XKKEBE
                                             0.003626
              18894
                    B003FSPWXY
                                             0.003173
               4701
                      B0048IPR9Y
                                             0.002770
               17127
                     B008FSIHNG
                                             0.002756
              13021
                     B001EPQ8XS
                                             0.002741
```

0.002572

0.002498

0.002466

0.002433

35800

13806

19006

7881

B00290W1CY

B000FFIIYU

B003R0LM48

B000VZJJIS

In [57]: food_df_mock.head() Out[57]: ProductId ProfileName Score Text HelpfulnessNumerator HelpfulnessDen Works with chicken 151 Chris 0 B00374XSVY 5 fish beef or pork. Fast eas... This kettle chips taste 637 B000G6RYNE Chris "Good, 0 Crispy & Crunc... I really like the **729** B008BEGP9W 0 Chris pineapple shortcakes sold he... These are just like **1006** B002XG21MO Chris 0 the animal crackers we eat... This product is as good **3142** B000FDKQCY Chris 5 0 as any that I have eve... merged_df_mock = scored_asin_df_mock.merge(food_df_mock, on='ProductId', f In [58]: merged_df_mock[['ProductId', 'RecommendationScore']].sort_values(["Recommer In [59]: Out[59]: ProductId RecommendationScore B001EW5YQS 0.025583 649 1122 B0042395CA 0.012464 5653 B000FVVZ3U 0.008445 5023 **B000IKEGRK** 0.005815 4366 B002DHN1UE 0.005210

Above are the top 5 items that Chris will be interested in purchasing for reviewing.

Conclusion

In this project, I successfully conducted sentiment analysis on the Amazon Fine Food Reviews dataset using Jupyter Notebooks and various natural language processing techniques. Our main objective was to recommend new products to someone who does reviews often (Chris), using RNN to perform sentiment analysis using only Amazon reviews as the model. I began by performing exploratory data analysis to gain insights into the dataset's characteristics and distribution of sentiments. Preprocessing steps, such as removing stop words, were applied to clean the text data and enhance the quality of our sentiment analysis. This analysis provided valuable insights into the key factors driving positive or negative sentiment within the Amazon Fine Food Reviews dataset.

The Sentiment Analysis on Amazon Fine Food Reviews project successfully employed deep learning techniques to classify customer reviews as positive or negative. The outcome of this project contributes to a better understanding of customer sentiments and can be potentially applied in various industries for customer feedback analysis and decision-making processes. Overall, this project was a success.